Evaluation of satellite algorithms for Chlorophyll-a concentration in the Northeastern Arabian Sea: A validation approach

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Abstract

Primary productivity of an aquatic system like Arabian Sea is broadly determined by the concentration of Chlorophyll-a (Chl-a/Ca) pigment. The present study is essaying to validate the Chl-a data set of prominent ocean color sensors (OC3M - MODIS, OC-OCM2, and OC3V-VIIRS) with sea truth data, collected from 204 stations for three year period (2015-2017). The in-situ concentrations of Chl-a depicts the geographic region under the mesotrophic and eutrophic spans ((0.1>Ca>1.0 mg m-3). The ratio of CaOCM2/CaIn-situ is 0.97±0.27 mg m-3 (n=199), in unsimilarity with CaVISSR/CaIn-situ is 1.75±0.79 mg m-3 (n=170) and CaMODIS/CaIn-situ is 2.53±1.42 mg m-3 (n=158). The regression analysis proclaims a moderate significant relationship for MODIS (r2 = 0.36; p<0.001), followed OCM2 (r2 = 0.32; p<0.001) and VISSR (r2 = 0.19; p<0.001) with evident overestimation (MODIS and VIRRS) and in tune (OCM2) with the satellite-derived datasets. The global ocean color missions aimed to set RMSE error at 0.35, the OCM2 shown the lowest RMSE as 0.13, which is relatively lower than the reference error limit. In overall performance among three algorithms, the OCM2 will provide a better estimation of Chl-a with a prediction of 32% accuracy and 34.37 % of bias. The log bias values for MODIS (0.35) and VIIRS (0.20) algorithms indicating the overestimation of Chl-a with in-situ concentrations, but the OCM2 algorithm is suitable in the region with a negligible bias of -0.03. The biogeochemical processes and ecosystem characteristics are dynamic from region to region, as yet in its urgent need to validate global and formulate regionally tuned algorithms periodically.

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Key Points:

- The study generates *In-situ* Chlorophyll-*a* for the northern Arabian Sea, which is missing link to understand the productivity dynamics
- Overestimation (RMSE and Bias) of Chlorophyll-*a* was observed for the global sensors like, MODIS and VIIRS.
- The OCM2 sensor performed better (34.4% bias and 32% variance) incompare with other MODIS and VIIRS sensors in the region

Abstract

Primary productivity of an aquatic system like Arabian Sea is broadly determined by the concentration of Chlorophyll-*a* (Chl-*a*/C_a) pigment. The present study is essaying to validate the Chl-*a* data set of prominent ocean color sensors (OC3M - MODIS, OC-OCM2, and OC3V-VIIRS) with sea truth data, collected from 204 stations for three year period (2015-2017). The *in-situ* concentrations of Chl-*a* depicts the geographic region under the mesotrophic and eutrophic spans ((0.1>C_a>1.0 mg m^{-3}). The ratio of $C_a^{OCM2}/C_a^{In\text{-}situ}$ is 0.97±0.27 mg m^{-3} (n=199), in unsimilarity with $C_a^{VISSR}/C_a^{In\text{-}situ}$ is 1.75±0.79 mg m^{-3} (n=170) and $C_a^{MODIS}/C_a^{In\text{-}situ}$ is 2.53±1.42 mg m^{-3} (n=158). The regression analysis proclaims a moderate significant relationship for MODIS (r^2 = 0.36; p<0.001), followed OCM2 (r^2 = 0.32; p<0.001) and VISSR (r^2 = 0.19; p<0.001) with evident overestimation (MODIS and VIRRS) and in tune (OCM2) with the satellite-derived datasets. The global ocean color missions aimed to set RMSE error at 0.35, the OCM2 shown the lowest RMSE as 0.13, which is relatively lower than the reference error limit. In overall performance among three algorithms, the OCM2 will provide a better estimation of Chl-*a* with a prediction of 32% accuracy and 34.37 % of bias. The log bias values for MODIS (0.35) and VIIRS (0.20) algorithms indicating the overestimation of Chl-*a* with in-situ concentrations, but the OCM2 algorithm is suitable in the region with a negligible bias of -0.03. The biogeochemical processes and ecosystem characteristics are dynamic from region to region, as yet in its urgent need to validate global and formulate regionally tuned algorithms periodically.

Plain Language Summary

The Arabian Sea is one of the most productive oceanic regions of the world. As of now, Chlorophyll-a is considered a key pigment and proxy to biological productivity in the ocean. The known fact is Chlorophyll-a pigment forms as base and fuels energy to the ocean food web. The in-situ estimation of Chlorophyll-a at realtime for the vast spatial scale will be logically impossible and economically unbearable. The ocean color remote sensing techniques pave many paths to estimate chlorophyll-a for the global oceans at different temporal and spatial resolutions. In the past three decades, many algorithms and sensors came up in the arena of ocean color remote sensing at both the global and regional levels. The concentrations of Chlorophyll-a pigment in the ocean system are spatiotemporally highly dynamic, influenced by various biogeochemical, Oceano-physical, and human-induced factors. The algorithms developed at the global scale may not suitable, which required continuous in-situ data to develop regional algorithms and also to refine global algorithms. In the current study, we aimed to generate the in-situ Chlorophyll-a dataset and also validated the performance of three sensors, i.e., MODIS, VIIRS, and OCM2. The results depict as overestimation of Chlorophyll-a was observed for the global sensors like MODIS and VIIRS. The OCM2 sensor performed better in comparison with MODIS and VIIRS sensors in the northern Arabian Sea. However, the large in-situ data sets are required to calibrate regional specific algorithms to estimate Chlorophyll-a more accurately in the northern Arabian Sea. In consideration of the field level practical difficulties, the in-situ sampling protocols (Standard Operating Procedures, SOPs) need to be formulated as per the international standards (JGOFS) among the diverse organizations engaged in the field of validation experiments with an objective of a uniform dataset.

1. Introduction

The major driving force to restraint the earth's climate is an ocean, but the extent of interaction is limited in understanding. The major bottleneck issue to understand the biogeochemical process is due to limited onboard cruises and other available ocean-based platforms. The data collected by satellite born ocean color sensors will provide a synoptic view to the researchers on physico-chemical and biological changes with the higher resolutions of spatial and temporal scales (Werdell 2003). To get an insight of the ocean carbon cycle, a precise assessment of phytoplankton biomass in the oceans is required. A large number of in-situ data observations are required to validate the satellite products to build up algorithms (Lavigne 2012). With the advancement of satellite technology and development of precise sensors viz. MODIS (Moderate Resolution Imaging Spectroradiometer; Esaias et al., 1998), OCTS (Ocean Colour and Temperature Sensor, Tanii et al., 1991), MERIS (Medium Resolution Imaging Spectrometer, Rast and Bezy, 1995) and SeaWiFS (Sea-viewing Wide Field-of-view Sensor, McClain et al., 1998), the application of the same has taken a flight, especially in the coastal and marine research. The ability of remote sensing technology to cover wider spatio-temporal realms have made them the method of choice in marine ecological study. Productivity is one of the most sought for ecological parameters by the marine researchers to explain various aspect of the ecosystem like seasonal variation in biomass of higher trophic organism, carrying capacity of the system, establishing interrelationship between physical and biological processes etc. Chlorophyll-a concentration is most often used as a proxy for the primary productivity of the aquatic system and hence several algorithms have been worked out to estimate the same from the remotely sensed products. The colour of the water of an aquatic system if basically a function of concentration of components like organic carbon, pigments from phytoplankton, and other particulate matters (Morel and Prieur, 1977). In-situ data as ground truth can be used to validate and calibrate the satellite products and one such effors was attempted by NASA Ocean Biology Processing Group and they maintains a repository of bio-optical data in a system in the SeaWiFS Bio-optical Archive and Storage System (Werdell and Bailey, 2005).

Oceanic system plays a very prominent role in Earth's Carbon cycle and budget and in order to decode the same one need to have fair understsnding about the magnum and the rate of primary production on global scale and also in diverse and unquie sub-systems of oceans (Prasad and Haedrich, 1994). The estimation of Chlorophyll-a and its variation over wider spatial and temporal scale becomes imperative in order to understand the global carbon budget (Platt et al., 1991; Tomlinson et al., 2004; Sarmiento et al., 2004). The phytoplankton plays a vital role in the global carbon cycle; it's high time to analyze the Spatio-temporal distribution and variability of Chl-*a* concentration for modern oceanography (Claustre et al. 2010). Although Chl-*a* is the most abundant biological oceanic measurement, however, the data generated is scarce in comparison with the number of other physical observations studied (e.g., temperature and salinity). In recent past years, many research studies have been attempted on the empirical relationship between satellite-derived ocean color and in-situ Chl-*a* concentration (Clark 1981).

In most of the attempts to validate satellite derived Chl-a, the regional field data (ground truths) are limited from single to few filed trips (Barbini et al., 2005). There exists a need of high quality in-situ data over larger temporal and spatial scale, if existing alogorithms are to be validated and newer ones are to be developed. The Arabian Sea marine ecosystem is uniquie in more than one way, it is under marked continental influence and have profound effect on monsoon which propels perennial productivity by ensuring vertical mixing of nutrients (Banse and English, 2000). The ground truth sampling is consorting with many hiccups like disparities in sampling protocols, spatial coverage, time management, huge cost, sampling errors, the paucity of wide-ranging observations, etc. The global algorithms were developed for the ocean color products (SeaWiFS, MODIS Terra, MODIS Aqua, OCM2, and VIIRS), which provides a synoptic view of the globe even with the prevalence of existing limitations. Presently there are few scattered ground-truth datasets available in the sphere of the globe, which are vital for the development of regional specific algorithms and support the validation of global ocean color missions. There were very scanty in-situ data sets are accessible in the present study region (Noora Al-Naimi et al. 2017; Raman M. 2013), and absolutely no validation trials were attempted for available ocean color products prior. The key objective is to enhance the knowledge of satellite algorithm deficiency in ocean color satellite products in the region. The current piece of work is purported to evaluate the performance in the variability between the ocean color satellite algorithm (MODIS, OCM2, and VIIRS) with ground truth data in the northeastern Arabian Sea.

2. Materials and Methods

2.1. Sampling design

The inadequacy of *in-situ* data sets will limit the ability to produce robust and accurate algorithms and validation of satellite-based Chl-*a* concentration at regional scale. The study area located in the northwest coast of India's Exclusive Economic Zone (EEZ), which comes under the northeastern Arabian Sea. The *in-situ* sampling was carried out at two locations, i.e., off Veraval and Okha coasts, Gujarat (Arabian Sea; Figure. 1a, 1b, 1c, 1d). On-board scientific sampling cruises conducted at monthly temporal intervals for a period of three years (2015 to 2017). The *in-situ* samples were collected randomly from the 204 sampling stations during the study period, but a few numbers of samples were able to analyzed during the monsoon season (June-September) due to the erratic sea conditions. To understand the temporal variations in Chl-a, separated the dataset into four main seasons, i.e., winter monsoon (December-March), spring inter-monsoon (April-May), Monsoon (June to September) and fall inter-monsoon (October-November) (Raman M. 2013).

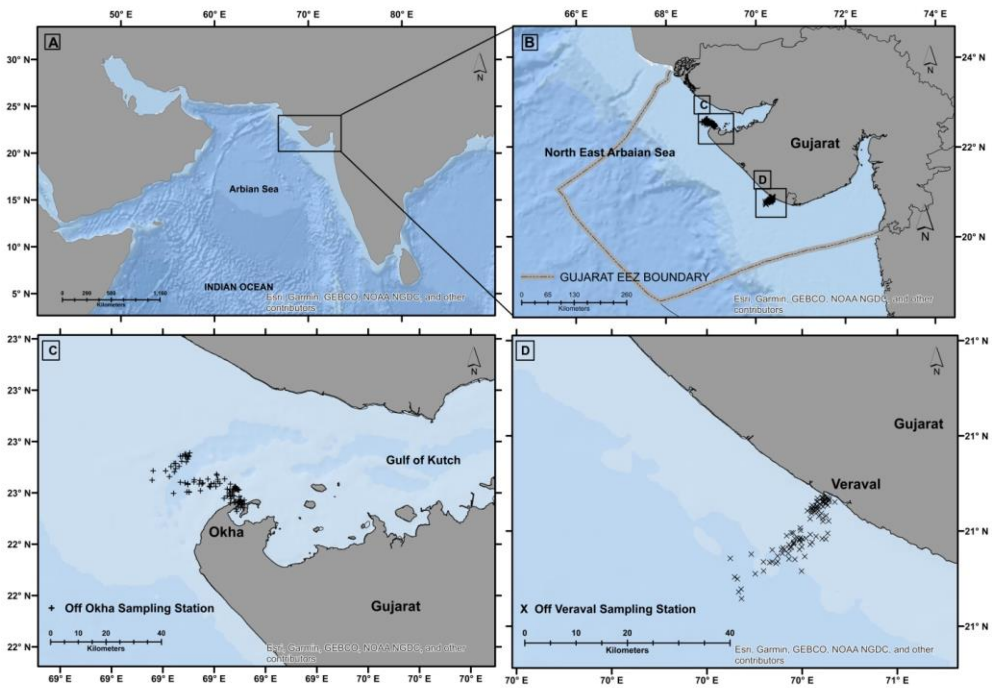

Figure 1. Map of the sampling area (a). Overview of Arabian Sea b) Sampling locations in the northeastern Arabian Sea (c). Detailed spatial distribution of sampling points at station 1 (off Okha) (d). Detailed spatial distribution of sampling points at station 2 (off Veraval)

3. Types of Data and Analysis

3.1. Estimation of In situ Chlorophyll a concentration

The most practised conventional approaches to measure Chl-*a* are: fluorometry (Holm-Hansen et al. 1965), spectrophotometry (Lorenzen 1967) and chromatography (Mantoura and Llewellyn 1983) different levels of accuracy and precision. Among three approaches, the most accurate method was high-performance liquid chromatography (HPLC, Hooker, et al. 2009), which provides the concentrations of a large spectrum of phytoplankton accessory pigments in addition to Chl-*a*. Fluorescence method is the only one that has not been included in the global reanalysis of Chl-*a*, for example, open ocean climatologies among the three main approach methodologies that exist for measuring Chl-*a* (i.e., water sampling, ocean color, and induced fluorescence), (Gregg and Conkright 2001). The spectrophotometric approach was adopted to evaluate the performance of Chl-*a* value of different satellite sensors because we aimed principally to analyze Chl-*a*, not for any pigments.

Triplicate surface water samples (0.5 liters for each) were collected at each sampling station. After collection, water samples were protected from sunlight and stored in chilled water to arrest the degradation of Chlorophyll-*a* pigments on-board. The collected samples were properly labeled on-board and kept in the icebox with gel ice in the dark and cold region in the boat. The sample holding time was about four hours before to reach the laboratory for filteration and further analysis. Samples were filtered through 47 mm GF/F filter paper using vacume filter for immediate filteration to avoid time lag. Followed, place the filter paper in a 90% acetone solution, later it was kept in the dark for 24 hrs in a refrigerator. The extracted material was separate using a centrifuge (R 24 Research Centrifuge, REMI, India) and the absorbance concentration was calculated by using a spectrophotometer at different wavelengths 750nm, 665nm, 645nm, and 630 nm (EPOCH2TC Microplate reader, Biotech, USA) (Vase V. K. 2018).

3.2. Satellite/In-situ matchups

A total of 204 *in-situ* data points are mapped to a rectangular projection with approximately four km^2/pixel in the northeastern Arabian Sea (20.72-22.62°N and 68.80–70.40°E). For comparability analysis between satellite and *in-situ* data, we have collected all images of Moderate Resolution Imaging Spectro-radiometer (MODIS) of NASA, Visible Infrared Imaging Radiometer Suite (VIIRS) of NASA and Ocean Color Monitor on-board OCEANSAT-2 of ISRO (OCM2). Out of a total *in-situ* data points, the obtained matchups for the satellite products are, i.e., MODIS (n=158), VIIRS (n=170) and OCM2 (n=199) due to the sun glint, temporal mismatch of satellite coverage, cloudy/haze, and monsoonal conditions during the sampling period. The 8-day composite L3 Chl-*a* data product with the high-resolution of $\sim$ 4 km^2/pixel was retrieved to evaluate the variability in the region. A stringent comparison between satellite and *in-situ* data should limit the time difference between the two measurements to within

± 2–3 h. The *in-situ* Chl-*a* dataset was match-up in time (8-day temporal composite matchup) and spatial (latitude and longitude) with the satellite-derived dataset (Noora Al-Naimi et al. 2017). The 8-day composite products were preferred for the region instead of daily satellite data, while the temporal threshold may not decrease the accuracy (Johnson et al. 2013)

3.3. Statistical analysis

Matchups between the *in-situ* and various satellite data of Chl-*a* concentrations were compared with assorted available global algorithms (Table 1) to understand the disparities/similarities in correlation, variability in data, accuracy, and error.

Table 1. Comparison of the relationships between satellite-derived with *in-situ* Chlorophyll-*a* concentration (mg m^{-3}) along different regions

Sensor/ Algorithm	N	Ratio (SIQR)	MAPD (%)	Log Bias (%)	Log RMSE	Bias	RMSE	Slope	R2	Study region	Reference
SeaWiFS	1293	0.998 (±0.267)	33.09	--	--	--	0.638	0.95	0.796	Global	Bailey, S. W, and Werdel, P.J., 2006
SeaWiFS – deep waters	271	0.922 (±0.239)	25.96	--	--	--	0.406	0.90	0.833	Global	Bailey, S. W, and Werdel, P.J., 2006
OC2	30	--	47.17	-1.30	23.50 %	--	--	0.43	0.450	Arabian Sea	Raman Mini, 2013
OC4	30	--	30.87	-6.00	20.90 %	--	--	0.56	0.590	Arabian Sea	Raman Mini, 2013
OC-OCM	30	--	22.34	-0.05	16.10 %	--	--	0.89	0.760	Arabian Sea	Raman Mini, 2013
VIIRS	30	--	--	--	--	--	--	--	0.358	Southern Ocean	Zeng C., et al., 2016
MODIS	24	--	--	--	--	--	--	--	0.175	Southern Ocean	Zeng C., et al., 2016
SeaWiFS	987	0.15	29.30	--	--	--	--	--	0.670	Sargasso Sea	Lavigne, H. et al., 2012
SeaWiFS	491	0.30	41.20	--	--	--	--	--	0.700	North western Mediterranean sea	Lavigne, H. et al., 2012
SeaWiFS	1113	0.16	29.40	--	--	--	--	--	0.630	North Pacific	Lavigne, H. et al., 2012
SeaWiFS	307	0.55 0.63	--	-0.36	0.44	-45.20	77.20 %	2.56	0.680	Southern Ocean	Marrari, M. et al., 2006
SeaWiFS	262	--	27.30	--	--	--	0.567	1.03	0.849	Global	Werdell, P.J., 2003
MODIS-Aqua	30	--	--	--	0.64	--	--	--	--	Gulf of Gabes	Hattab et at., 2013
MODIS-Aqua	114	--	--	--	0.38	--	--	--	--	Northern South China Sea	Shang et al., 2014
MODIS-Aqua	50	--	--	--	0.31	--	--	--	--	Eastern Arabian Sea	Tilstone et al., 2013
MODIS-Aqua	85	--	--	--	0.18	--	--	--	--	Red Sea	Brewin et al., 2013
VIIRS	38	--	--	--	0.23	--	--	--	--	California Current Bed	Kahru at al., 2014
VIIRS	29	--	--	0.24	0.32	--	--	--	0.795	Central Arabian Gulf	Noora Al-Naimi et al., 2017

OC3	28							-0.11	0.114	Ardley Cove (Antarctica)	Zeng C. et al., 2017
MODIS-Aqua	158	2.53 (±1.42)	192.39	0.34	0.41	294.02	427.81%	3.73	0.360	North eastern Arabian Sea	Present study
OCM2	199	0.97 (±0.27)	35.01	-0.03	0.13	34.37	49.01 %	0.40	0.320	North eastern Arabian Sea	Present study
VIIRS	170	1.75 (±0.79)	142.94	0.20	0.28	154.88	212.72%	1.25	0.190	North eastern Arabian Sea	Present study

The performance indices like a satellite to *in-situ* ratio, median of satellite to *in-situ* ratio, semi-interquartile range (SIQR), median absolute percentage difference (MPD) were computed to make out the overestimation/underestimation of Chl-*a* for satellite data sets. The SIQR provides an indication of the spread of the data and reveals the measure of uncertainty with additional information on how accurately the satellite retrieval agrees with *in-situ* measurements.

$$SIQR = \frac{Q_3 - Q_1}{2}$$

Where Q_1 is the 25th percentile, and Q_3 is the 75th percentile (Q_2 would be the median value). The median ratio indicates an overall bias. The median absolute percentage difference (MPD) is calculated as the median of the individual absolute percentage differences and calculates as (Bailey and Werdell 2006):

$$PD_i = 100 * \frac{|X_i - Y_i|}{Y_i}$$

where X is the satellite value, and Y is the *in-situ* value

Principally, two estimates used to assess the differences between the *in-situ* and satellite-derived data. First, the root mean square (RMS) and the mean difference (bias) in percentage (Marrari et al. 2006):

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i)^2} \times 100$$

$$bias = \bar{x} = \left(\frac{1}{n}\sum_{i=1}^{n} x_i\right) \times 100$$

$$x = \frac{S - I}{I}$$

where *S* is the satellite data, *I* is in *situ-data*, and n is the number of data pairs. For a normally distributed x, RMS should equal the standard deviation. Further, because the natural distribution of Chl-*a* is lognormal (Campbell 1995), error estimates were also made on the logarithmically transformed (base 10) data:

$$\log\_RMS = \sqrt{\frac{\sum\left[\left(log(S) - log(I)\right)\right]^2}{n}}$$

$$\log\_bias = \frac{\sum[log(S) - log(I)]}{n}$$

Generally, error estimates cannot be expressed as percentages because they are transformed logarithmically. These error estimates have been used in recent publications to describe the performance of the ocean color algorithms (O'Reilly et al. 2000) and to validate SeaWiFS global and regional estimates of Chl-*a* (Zhang et al. 2006).

4. Results

The significant temporal variations (monthly) were depicted in Figure 2, illustrating the maximum during the winter monsoon (1.52±0.48 mg m^{-3}) and minimum during the monsoon season (1.25±0.50 mg m^{-3}). The representation of log_Chl-*a* data as a histogram plot depicts the present study region under the Mesotrophic and Eutrophic category (Chl-*a* concentration of >0.1 mg m^{-3}) (Figure 3). The median of Chl-*a* value was highest for the MODIS at 2.92 mg m^{-3} (ranged from 0.28 to 18.75 mg m^{-3}), followed by VISSR as 2.43 mg m^{-3} (ranged from 0.36 to 11.82 mg m^{-3}), OCM2 as 1.35 mg m^{-3} (ranged from 0.57 to 2.38 mg m^{-3}) and *in-situ* as 1.36 mg m^{-3} (ranged from 0.50-2.96 mg m^{-3}) (Table 2; Figure 4).

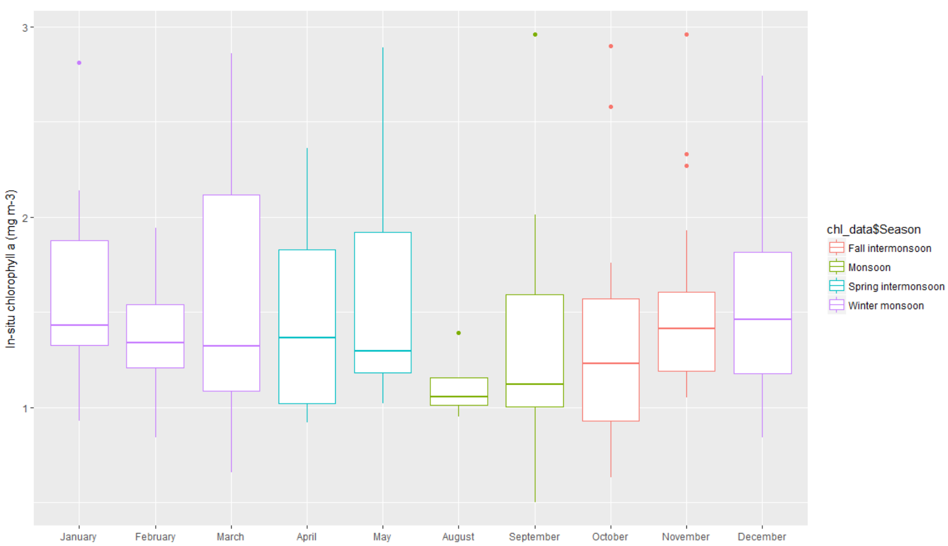

Figure 2. Temporal variations (monthly and seasonal) in *in-situ* Chl-*a* (mg m^{-3}) in the study region

Table 2. Descriptive statistics of *in-situ* and satellite derived Chl-*a* used in the study (mg m^{-3})

Algorithm	n	Range	Q1	Q3	Mean ± SE	Median	SD	IQR	CV (%)
In-situ	204	0.50-2.96	1.08	1.75	1.46±0.04	1.36	0.502	0.668	34.38
MODIS	158	0.28-18.75	2.49	4.14	3.94±0.25	2.92	3.118	1.645	79.12
OCM2	199	0.57-2.38	1.08	1.61	1.34±0.02	1.35	0.35	0.527	26.06
VIIRS	170	0.36-11.82	2.04	2.85	2.55±0.11	2.43	1.462	0.803	57.38

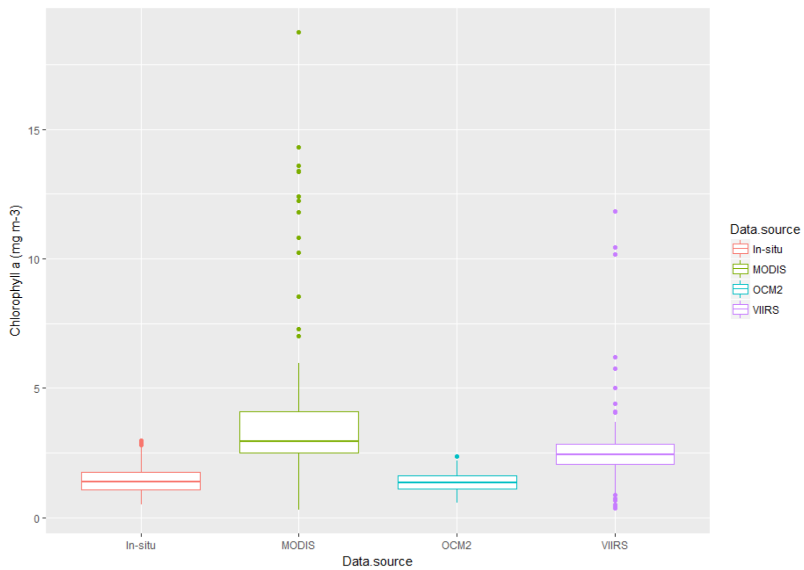

Figure 3. Boxplot indicates Chlorophyll-*a* (mg m^{-3}) concentrations for *in-situ* and satellite datasets

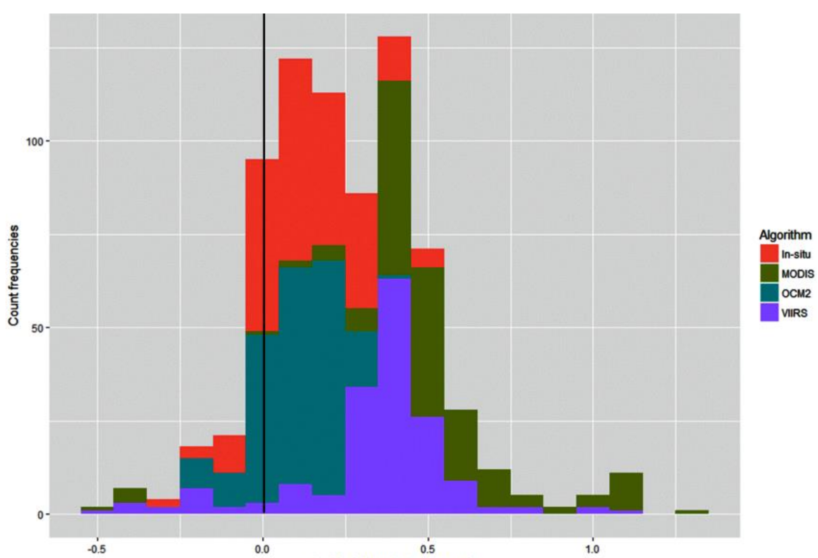

Figure 4. Log Chlorophyll-*a* distribution histogram for the various datasets. The vertical line at 1.0 mg m^{-3} (0.0 in log) delineate data from the mesotrophic and eutrophic regions

The mean ratio of $C_a^{OCM2}/C_a^{In\text{-}situ}$ is closer to 1 with narrow deviation (i.e., 0.97±0.27 mg m^{-3}), in contrast to the higher ratio for $C_a^{VISSR}/C_a^{In\text{-}situ}$ (1.75±0.79 mg m^{-3}) and $C_a^{MODIS}/C_a^{In\text{-}situ}$ (2.53±1.42 mg m^{-3}), which depicts the overestimation of Chl-*a* for the satellite dataset (Figure 5). The correlation analysis between the in-situ and satellite Chl-*a* data set revealed a better correlation between *in-situ* vs. MODIS (0.602, p<0.001), *in-situ* vs. VIIRS (0.589, p<0.001), *in-situ* vs. OCM2 (0.562, p<0.001) (Figure 6). The OCM2 satellite product is having less uncertainty in comparison with the other datasets in the region.

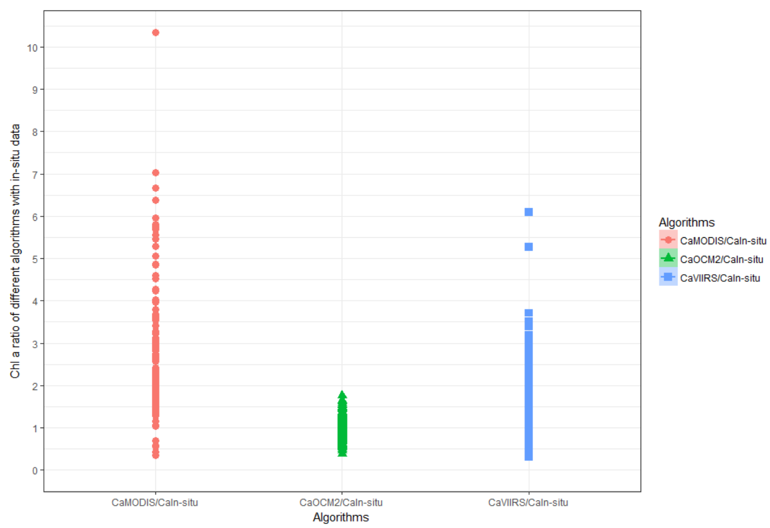

Figure 5. The plot indicates the ratio of Chl-*a* between in-situ and satellite data products in the region

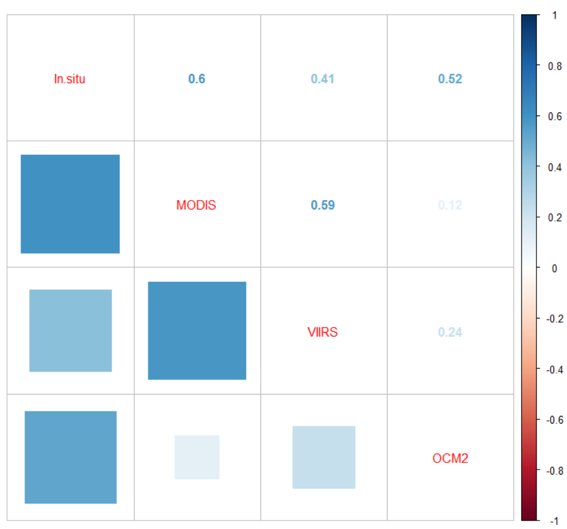

Figure 6. Correlation plot between the *in-situ* and satellite derived Chl-*a* (mg m^{-3})data in the region

The strew of mean absolute percentage differences (MAPD) between three different algorithms, and *in-situ* measurements shown in the Table. 3. The lower MPD value was estimated for the OCM2 (35.01%), which is having better accuracy with the *in-situ* data than the other sensors, i.e., VISSR (142.94%) and MODIS (192.39%). The bias percentage is lower in the case of C_a^{OCM2} at 34.37%, followed by C_a^{VISSR} (154.88%) and C_a^{MODIS} (294.02%). The RMS error was observed lower for the OCM2 (49.01%), followed by VISSR (212.72%) and MODIS (427.81%). Overall, the bias errors are significantly lower for OCM2 than other datasets (MODIS and VISSR). The slope, coefficient of determination (r^2), and root mean square of the regression (RMSE) are listed in Table 3 for the scatter plots of satellite Chl-*a* data with *in-situ* values (Fig. 7). The SIQR is an indication of the uncertainty of the satellite and *in-situ* Chl-*a* value, and the lower uncertainty was observed in C_a^{OCM2} vs. $C_a^{In\text{-}situ}$ (0.27 mg m^{-3}), followed by C_a^{VISSR} vs. $C_a^{In\text{-}situ}$ (0.79 mg m^{-3}) and C_a^{MODIS} vs. $C_a^{In\text{-}situ}$ (1.42 mg m^{-3}). The C_a^{OCM2} is nearly scattering around the 1:1 regression line, but a scatter pattern was observed with other datasets $C_a^{VISSR}/C_a^{In\text{-}situ}$ and $C_a^{MODIS}/C_a^{In\text{-}situ}$.

Table 3. Validation statistics of the matchups of Chlorophyll-*a* (mg m^{-3}) performed in the northeastern Arabian Sea

Parameter	C_a^{MODIS} **vs.** $C_a^{In\text{-}situ}$	C_a^{OCM2} **vs.** $C_a^{In\text{-}situ}$	C_a^{VIIRS} **vs.** $C_a^{In\text{-}situ}$
Ratio (±SIQR)	2.53 (±1.42)	0.90 (±0.27)	1.75 (±0.79)
MPD (%)	192.39	35.01	142.94
Bias	294.02	34.37	154.88
RMSE	427.81	49.01	212.72
Log_bias	0.348	-0.031	0.200
Log_RMSE	0.411	0.126	0.284
a	-1.69	0.76	0.68
b	3.73	0.40	1.25
R^2	0.36	0.32	0.19

The high r^2 and slopes close to unity suggest that the validation comparisons are in agreement with the measured dynamic range. The slope values are significantly deviating from the unity in case of three regression equations, i.e., MODIS (3.73), VISSR (1.25), and OCM2 (0.40). The highest slope value was noticed for the MODIS algorithm due to the widespread of data (0.28 to

18.75 mg m^{-3}). The r^2 values for the three regression equations are not so strong, but shown significant variability ($p<0.001$), out of which the highest value was observed for MODIS (r^2 = 0.36), next to OCM2 (r^2 = 0.32) and VISSR (r^2 = 0.19) (Table 3 and Figure 7). Out of the three algorithms observed, the MODIS can explain the highest of 36.0% of the variability of *in-situ* Chl-*a*, followed by OCM2 (32.0%) and VISSR (19.0%). The scattered plots symbolize the wide distribution of regression points around the 1:1 line. The expression of RMSE for the log-transformed data of three different algorithms concerning *in-situ* values depicted the overall uncertainty and observed highest for MODIS (0.411), VISSR (0.284), and smaller for OCM2 (0.126) (Table 3).

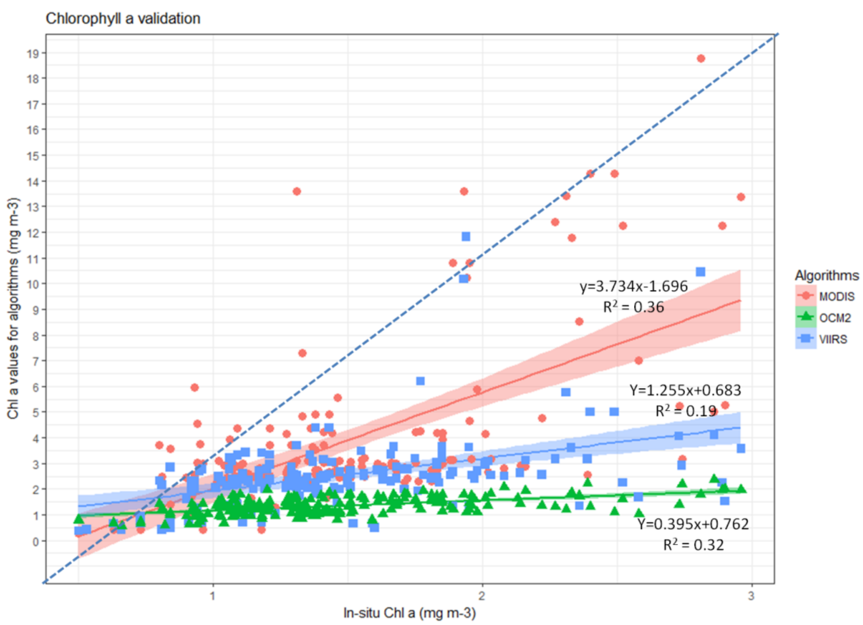

Figure 7. Scatter plot between satellite estimated algorithms (MODIS, OCM2 & VIIRS) and *in-situ* Chlorophyll-*a* (mg m^{-3}) in the northeastern Arabian Sea

5. Discussion

The satellite-derived maps provide a unique temporal and spatial picture of the Chl-*a* at a global scale (McClain et al. 1998). Methodologies were developed by OBPG to validate many historical and operational ocean color missions and the datasets which can be used for global climate studies, in such cases a high-quality data set covering a multi-year period is must (Bailey and Werdell 2006). The global accuracy in case of clear and natural waters by modern sensors for the Chlorophyll-*a* was defined in the range of 5% to 35%, (Hooker et al. 1992). Marina, M., 2006, has reported that the surface Chlorophyll-*a* concentration (C_a, mg m^{-3}) in the Southern Ocean was significantly lower than *in-situ* water samples and also revealed the percentage overestimation of *in-situ* data would increase with the decrease in concentrations. However, satellite observations are limited to the ocean surface, and the error was calculated by matchup analysis of concurrent satellite and *in-situ* measurements, which was evaluated to vary around ±35 % in the open ocean (Moore et al. 2009). Antoine et al. (1996) classify the geographic diversity into three trophic regimes based on the Chl-*a* concentration, i.e., oligotrophic ($C_a \leq 0.1$ mg m-3), mesotrophic ($0.1 < C_a \leq 1.0$ mg m^{-3}) and eutrophic ($C_a > 1.0$ mg m^{-3}). The *in-situ* measurements of the represented the northeastern Arabian Sea falls under the two spans, i.e., mesotrophic and eutrophic ($0.1 > C_a > 1.0$ mg m^{-3}), which explains the region with better productivity. The present study region located amid two gulfs, i.e., Gulf of Kutch and Gulf of Kambath, where vertical mixing of nutrients will take place, which supports better primary productivity. The possible reasons for the high productivity due to the coastal upwelling due to monsoon winds (Swallow 1984) and convective mixing of dense north waters due to northeast monsoon (Kumar and Prasad 1996).

In the study region, the range of Chl-*a* concentration was, i.e., *in-situ* (0.50 to 2.96 mg m^{-3}), MODIS (0.28 to 18.75 mg m^{-3}), VIIRS (0.36 to 11.82 mg m^{-3}) and OCM2 (0.57 to 2.38 mg m^{-3}), which are in similar ranges with the previous studies. The Chl-*a* data were acquired from encompassing, which is ranging from 0.012 to 72.12 mg m^{-3} (Werdell and Bailey 2005). The OC2v2 algorithm was used in the marginal west sea of the Antarctic Peninsula, for which the SeaWiFS imageries underestimate Chlorophyll-*a* (0.7–43 mg m^{-3}) concentrations by 60% (Dierssen 2000; Smith 2000). Along South Georgia region (54.5^0 S, 37^0 W) underestimation of 87% was found in the lower Chl-*a* concentration range (0–1.0 mg m^{-3}), but 30% underestimation was recorded for the Chl-*a* concentration values of >5 mg m^{-3} (Kwok and Comiso 2002). The Chl-*a* concentration varies from 0.5 to 7.1 mg m^{-3}, with an average value of 2 mg m-3 in the Godavari estuarine waters of India (Latha 2013). The Chl-*a* concentration of satellite data with *in-situ* values, the OCM2, had a similar range of Chl-*a* concentration in the region.

The permissible errors in the log-transformed C_a data during the algorithm development were about 0.2 or less, and nearly 60% root mean square (RMS) relative error (O'Reilly et al. 2000). In the global validation of C*a*, the error for most of the ocean basins is about 0.3 (Gregg and Cassey 2004), but in the case of the Southern Ocean, the reported errors are significantly larger. According to Raman M. (2013), the RMSE for the log-transformed data of satellite-derived versus *in-situ* Chl-*a* value was higher for OC2 (23.50%), OC4 (20.90%) and OC-OCM

(16.10%). The present results, i.e., log bias and log RMSE percentage are coherent with the previous studies for different algorithms MODIS (log bias is 0.348 & log RMSE is 41.10 %); VIIRS (log bias is 0.200 & log RMSE is 28.40 %) and OCM2 (log bias is -0.031 & log RMSE is 12.60 %). The OCM2 sensor performed better for the estimation of Chl-*a* in the region with lower log RMSE and log bias values than the other two sensors, i.e., MODIS and VIIRS. A comparative analysis of Chl-*a* during bloom and non-bloom periods of phytoplankton were studied along Ardley Cove, King George Island, observed as maximum Chlorophyll-*a* reached 9.87 mg m-3 during the bloom period. But, the average Chlorophyll-*a* concentration observed was less than 2 mg m^{-3} during 1991 to 2009. In case of high latitude and high Chlorophyll-*a* regions by the fluorescence approach, ensuing a better correlation at 59.46% (Chen Zeng 2017). The satellite measurements still have large errors in estimating phytoplankton biomass [Marrari et al. 2006] and the global chlorophyll-a satellite algorithm typically underestimates Chlorophyll-*a* in the Southern Ocean [Gregg and Casey, 2004; Friedrichs et al. 2009].

In many cases, it remains obvious to underestimate (>2.0 mg m^{-3} Chlorophyll-*a*) and overestimates (<2.0 mg m^{-3} Chlorophyll-*a*), but the RMS was surpasses by 60% for both OC3M and OC3V algorithms. The Chlorophyll-*a* data from MODIS and VIIRS sensors shown weak correlation with *in-situ* Chl-*a*. However, the VIIRS sensor still performs better than MODIS in the estimation of Chl-*a* with better regression coeffiecients. The little differences in band ratio was estimated by using sensitivity test while declare the selection of both MODIS and VIIRS (Chen Zeng 2016). The RMSE percentage measures the similarity/dissimilarity between the in-situ and satellite-derived Chl-*a* value, the OCM2 had lower RMSE (49.01 %) than the other algorithms, i.e., VIIRS (212.72%) and MODIS (427.81%). Various empirical algorithms have been developed successfully using regional data sets by considering the local geophysical conditions (Darecki and Stramski 2004; Garcia et al. 2005; Gohin et al. 2002). The current research attempt is to strengthen the *in-situ* database is in support of the above objective to develop practical algorithms.

The regression analysis shown significant variability in comparison with *in-situ* data, i.e., MODIS (r^2 = 0.36 and slope = 3.73), followed by OCM2 (r^2 = 0.32 and slope = 0.40) and VISSR (r^2 = 0.19 and slope = 1.25). Werdell (2003), attempted the validation trials for the SeaWiFS global data set with *in-situ* measurements and recorded error and regression parameters as a percentage difference (27.3%), RMSE (0.567), slope±SE (1.034±0.025) and r^2 (0.849). Chen et al. (2017) reported the OC3 global band ratio algorithm Chlorophyll-*a* estimation shown a non-linear relationship with *in-situ* values with an 11.43% correlation (y=-0.1094x+1.9846; R^2=0.1143) along the Southern Ocean. The algorithms which estimate Chlorophyll-*a* range from 0.1 to 10 mg m^{-3}, have a similar range with *in-situ* Chlorophyll-*a*. In the Antarctica Peninsula region, the OC3 algorithm coefficients shown better perfprmance (r^2 = 0.64) (Gabric 2005). In the present study, the variability between the satellite sensor and *in-situ* data sets is meliorate explicated. In contrast, the MODIS data set explains the highest of 36.0% of the variability of *in-situ* Chl-*a*, followed by OCM2 (32.0%) and VISSR (19.0%).

The validation trials of *in-situ* Chlorophyll-*a* and OCM-2 (OC2 and OC4V4 algorithms) shown a significant regression relationship (R^2=0.60) along the estuarine waters of the Bay of Bengal and also revealed overestimation at low Chl-*a* concentration and underestimation at high Chl-*a* concentration (Latha 2013). The mean absolute percentage differences for OC2, OC4, and OC-OCM datasets were observed at 47.17%, 30.87%, and 22.34% with *in-situ* Chl-*a* concentration. The coefficient of determination of R^2 of satellite estimated versus *in-situ* dataset was highest for OC-OCM (R^2=0.76; slope=0.89), followed by OC4 (R^2=0.59; slope=0.56) and OC2 (R^2=0.45; slope=0.43) (Raman M. 2013). The global ocean color missions aimed to set RMSE error at 0.35 (IOCCG 2000), the OCM2 shown the lowest RMSE error as 0.126, which is comparatively lower than the reference error limit. However, the OCM2 algorithm has a lower log bias (-0.03) than the other two algorithms, i.e., VISSR (0.20) and MODIS (0.35). The OCM2 product has negligible bias and good performance than the other two, i.e., VISSR and MODIS.

The most widely used global algorithms for the estimation of Chlorophyll-*a* were providing acceptable results when developed using a cohesive global data set (e.g., Maritorena et al. 2002). Massive gaps were exists in estimation of Chl-*a* using satellite sensors in compare with *in-situ* values. The accuracy performance by different algorithms studied in the region, the OCM2 shown better overall statistical indicators, i.e., MPD, RMSE, Bias, log bias, and log RMSE and regression coefficients than the other algorithms (MODIS and VIIRS). The global algorithms (MODIS and VIIRS) overestimate *in-situ* Chl-a concentration (mg m^{-3}), while the OCM2 algorithm is in tune with the *in-situ* values in the northeastern Arabian Sea. Overall, the satellite sensors (MODIS and VIIRS) are systematically overestimated Chl-*a* concentration in comparison with *in-situ* data, mainly due to the significant influence of sediments, CDOM, and land discharges. The validation exercise in the region suggests better accuracy indicators for the OCM2 algorithm and more suitable for the region's bio-optical characteristics.

5. Conclusions

Northern Arabian Sea is considered as the most productive region in the globe and with a unique bio-geochemical and oceanographical coupling process. Because of the region's productivity identity and scarcity of the *in-situ* data, the current study initiated to generate *in-situ* Chl-*a* dataset and also to evaluate the performance of ocean color satellite sensors in the region. In obvious, the validation process of the satellite datasets is coupled with many limitations, i.e., atmospheric correction due to cloud coverage and sun glint, lack of large in-situ dataset, the disparity in the in-situ data analysis methodologies, coverage of satellites in spatial and temporal scales and frequency of matchup points., etc. Aong three satellite sensors (MODIS, VIIRS and OCM2) evaluated in the region, the OCM2 sensor data set performed better than others (ratio is 0.97 ± 0.27 mg m^{-3}; bias is 34.37%; RMSE is 49.01 %; slope 0.40 and R^2 is 0.32 ($p<0.001$)). In relation with *in-situ* data, the MODIS (2.53 mg m^{-3}) and VISSR (1.75 mg m^{-3}) sensors indicate the overestimation of Chl-*a* concentration in the region, while the OCM2 (0.97 mg m^{-3}) sensor in a match with the ground truth data. The error bias in the case of the OCM2 sensor is comparatively lower than the global error accuracy limit (35%) and suggested to use in the region. However, the large *in-situ* data sets are required to calibrate regional specific algorithms to estimate Chl-*a* more accurately in the northeastern Arabian Sea. In consideration of the field level practical difficulties, the *in-situ* sampling protocols (Standard Operating Procedures, SOPs) need to be formulated as per the international standards (JGOFS) among the diverse organizations engaged in the field of validation experiments.

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References

Antoine, D., Andre, J. M., & Morel, A. (1996). Oceanic primary production: 2. Estimation at global scale from satellite (CZCS) chlorophyll. *Global biogeochemical Cycles, 10,* 57-70.

Barbini, R., Colal, F., Fantoni, R., Fiorani, L., Okladnikov, I. G., & Palucci, A. (2005). Comparison of SeaWiFS, MODIS-Terra, and MODIS-Aqua in the Southern Ocean. International Journal of Remote Sensing, *26(11)*, 2471−2478.

Brewin, R.J.W., Raitsos, D.E., Pradhan, Y., & Hoteit, I. (2013). Comparison of chlorophyll in the Red Sea derived from MODIS-Aqua and in vivo fluorescence. Remote Sens. Environ., *136*, 218–224.

Campbell, J. W. (1995). The lognormal distribution as a model for bio-optical variability in the sea. Journal of Geophysical Research, *100*, 13237−13254.

Chen, Z., Huiping, X., & Andrew, M. F. (2016). Chlorophyll-a Estimation Around the Antarctica Peninsula Using Satellite Algorithms: Hints from Field Water Leaving Reflectance. Sensors, *16*, 2075; doi:10.3390/s16122075.

Chen, Z., Tao, Z., Andrew, M. F, & Huiping, X. (2017). Fluorescence-Based Approach to Estimate the Chlorophyll-A Concentration of a Phytoplankton Bloom in Ardley Cove (Antarctica). Remote Sens., *9*, 210; doi:10.3390/rs9030210

Clark, D. K. (1981). Phytoplankton pigment algorithms for the Nimbus-7 CZCS. In J. F. R. Gower (Ed.), Oceanography from space (pp. 227 – 237). New York’ Plenum Press.

Claustre, H., Antoine, D., Boehme, L., Boss, E., D’Ortenzio, F., Fanton D’Andon, O., Guinet, C., Gruber, N., Handegard, N. O., Hood, M., Johnson, K., Lampitt, R., LeTraon, P.-Y., Leque´re´, C., Lewis, M., Perry, M.-J., Platt, T., Roemmich, D., Testor, P., Sathyendranath, S., Send, U., and Yoder, J. (2010). Guidelines Towardss an Integrated Ocean Observation System for Ecosystems and Biogeochemical Cycles, in: Proceedings of OceanObs’09: Sustained Ocean Observations and Information for Society (Vol.2), Venice, Italy, 21–25 September 2009, edited by Hall, J., Harrison, D. E., and Stammer, D., ESA Publication WPP^{-3}06, doi:10.5270/OceanObs09.pp.14, 2010.

Dierssen, H.M., & Smith, R.C. (2000). Bio-optical properties and remote sensing ocean color algorithms for Antarctic Peninsula waters. J. Geophys. Res. 2000, *105*, 26301–26312.

Esaias, W. E., Abbott, M. R., Barton, I., Brown, O. B., Campbell, J. W., & Carder, K. L. (1998). An overview of MODIS capabilities for ocean science observations. IEEE Transactions on Geoscience and Remote Sensing, *36*, 1250 – 1265.

Friedrichs, M.A., Carr, M.E., Barber, R.T., Scardi, M., Antoine, D., Armstrong, R.A., Asanuma, I., Behrenfeld, M.J., Buitenhuis, E.T., & Chai, F. (2009). Assessing the uncertainties of model estimates of primary productivity in the tropical Pacific Ocean. J. Mar. Syst. 2009, *76*, 113–133.

Gabric, A. J., Shephard, J. M., Knight, J. M. Jones, G., & Trevena, A.J. (2005). Correlations between the satellite-derived seasonal cycles of phytoplankton biomass and aerosol optical depth in the Southern Ocean: Evidence for the influence of sea ice. Glob. Biogeochem. Cycles 2005, 19, GB4018.

Garcia, C. A. E., Garcia, V. M. T., & McClain, C. R. (2005). Evaluation of SeaWiFS chlorophyll algorithms in the Southwestern Atlantic and Southern Oceans. Remote Sensing of Environment, *95*, 125 – 137.

Gohin, F., Druon, J. N., & Lampert, L. (2002). A five-channell chlorophyll concentration algorithm applied to SeaWiFS data processed by SeaDAS in coastal waters. International Journal of Remote Sensing, *23*, 1639 – 1661.

Gregg, W.W., & Casey, N.W. (2004). Global and regional evaluation of the SeaWiFS chlorophyll-a data set. Remote Sens. Environ. 2004, *93*, 463–479.

Gregg, W. W., & Conkright, M. (2001). Global seasonal climatologies of ocean chlorophyll: Blending in situ and satellite data for the Coastal Zone Color Scanner era, J. Geophy. Res.-Oceans, *106*, 2499–2515, 2001.

Lavigne, H., D'Ortenzio, F., Claustre, H., & Poteau, A. (2012). Towards a merged satellite and in situ fluorescence ocean chlorophyll product. Biogeosciences, *9*, 2111–2125, 2012. doi:10.5194/bg-9-2111-2012.

Hattab, T., Jamet, C., Sammari, C., & Lahbib, S. (2013). Validation of chlorophyll-α concentration maps from AquaMODIS over the Gulf of Gabes (Tunisia): Comparison between MedOC3 and OC3M bio-optical algorithms. *Int. J. Remote Sens.* 2013, *34*, 7136-7177.

Holm-Hansen, O., Lorenzen, C. J., Holmes, R. W., & Strickland, J. D. H. (1965). Fluorometric Determination of Chlorophyll, Ices J. Mar. Sci., 30, 3–15, doi:10.1093/icesjms/30.1.3, 1965.

Hooker, S.B., Esaias, W.E., Feldman, G.C., Greg, W.W., & McClain, C.R. (1992). An overview of SeaWiFS and ocean color. *NASA Tech. Memo., vol. 104566.*

Hooker, S. B., Van Heukelem, L., Thomas, C. S., Claustre, H., Ras, J., Schulter, L., Clementson, L., Van der Linde, L., Eker-Develi, E., Berthon J.-F., Barlow, R., Sessions, H., Ismail, H., and Perl, J. (2009). The third SeaWiFS HPLC Analysis Round-Robin Experiment (SeaHARRE^{-3}), NASA technical Memorandum 2009-215849, Greenbelt: NASA Goddard Space Flight Center, 2009.

IOCCG (2000). Remote sensing of ocean colour in coastal, and other optically-complex waters. In S. Sathyendranath (Ed.), *Reports of the International Ocean-Colour Coordinating Group, No. 3, IOCCG, Dartmouth, Canada* (140pp.).

Johnson, R., Strutton, P.G., Write, S.W., McMinn, A. & Meiners, K.M. (2013). Three improved satellite chlorophyll algorithms for the Southern Ocean. *J. Geophys. Res.* 2013, *118*, 3694-3703.

Banse, K., & D. C. English. (2000). “Geographical differences in seasonality of CZCS-derived phytoplankton pigment in the Arabian Sea for 1978–1986,” Deep-Sea Research Part II, vol. *47*, no. 7-8, pp. 1623–1677, 2000.

Korb, R. E., Whitehouse, M. J., & Ward, P. (2004). SeaWiFS in the Southern Ocean: Spatial and temporal variability in phytoplankton biomass around South Georgia. Deep-Sea Research, *51*, 99−116.

Kumar, S.P., & Prasad, T.G. (1996). Winter cooling in the northern Arabian Sea. Current Science, Vol. *71*, No, 11. pp. 834-841.

Kwok, R., & Comiso, J.C. (2002). Spatial Patterns of Variability in Antarctic Surface Temperature: Connections to the Southern Hemisphere Annular Mode and the Southern Oscillation. Geophys. Res. Lett. 2002, *29*, 1705.

Lorenzen, C. J. (1967). Determination of Chlorophyll and Pheo-Pigments: Spectrophotometric Equations, Limnol. Oceanogr., *12*, 343–346, 1967.

Mantoura, R. F. C., & Llewellyn, C. A. (1983). The rapid determination of algal chlorophyll and carotenoid pigments and their breakdown products in natural waters by reverse-phase high-performance liquid chromatography, Anal. Chim. Acta, 151, 297–314, doi:10.1016/S0003-2670(00)80092-6, 1983.

Marina, M., Chuanmin, H., & Kendra D. (2006). Validation of SeaWiFS chlorophyll a concentrations in the Southern Ocean: A revisit. Remote Sensing of Environment *105* (2006) 367 – 375.

Maritorena, S., Siegel, D. A., & Peterson, A. R. (2002). Optimization of a semianalytical ocean color model for global-scale applications. Applied Optics, *41*, 2705 – 2714.

Marrari, M.; Hu, C.; Daly, K. (2006). Validation of SeaWiFS chlorophyll-a a concentrations in the Southern Ocean: A revisit. Remote Sens. Environ. 2006, *105*, 367–375.

McClain, C. R., Cleave, M. L., Feldman, G. C., Gregg, W. W., & Hooker, S. B. (1998). Science quality SeaWiFS data for global biosphere research. Sea Technology, *39*, 10 – 15.

McClain, C., Cleave, M., Feldman, G., Gregg, W., Hooker, S., & Kuring, N. (1998). Science quality SeaWiFS data for global biosphere research, Sea Technol., 39, 10–16, 1998.

Moore, T. S., Campbell, J. W., & Dowell, M. D. (2009). A class-based approach to characterizing and mapping the uncertainty of the MODIS ocean chlorophyll product, Remote Sens. Environ., 113, 2424–2430, doi:10.1016/j.rse.2009.07.016, 2009.

Morel, A., & Prieur, L. (1977). Analysis of variations in ocean color. Limnology and Oceanography, *22*, 709 – 722.

Noora, Al-Naimi., Dionysios, E., Raitsos, R. B. H., & Yousria, S. (2017). Evaluation of Satellite Retrievals of Chlorophyll-a in the Arabian Gulf. Remote Sens. 2017, *9*, 301; doi:10.3390/rs9030301.

O'Reilly, J. E., Maritorena, S., O'Brien, M. C., Siegel, D. A., Toole, D., & Menzies, D. (2000). SeaWiFS postlaunch calibration and validation analyses: Part 3. SeaWiFS postlaunch technical report series, 11. In S. B. Hooker, & E. R. Firestone (Eds.), NASA Technical Memorandum 2000-206892 49 pp.

Platt, T., Caverhill, C., & Sathyendranath, S. (1991). Basin-scale estimates of oceanic primary production by remote sensing: The North Atlantic. Journal of Geophysical Research, *96*, 15147 – 15159.

Prasad, K. S., & Haedrich, R. L. (1994). Satellite-derived primary production estimates from the Grand Banks: Comparison to other ocean regimes. Continental Shelf Research, *14(15)*, 1677−1687.

Raman, M. (2013). Estimating primary production in the Arabian Sea using satellite derived data. Ph.D. Thesis. Mangalore University. p. 1-223.

Rast, M., & Be´zy, J. L. (1995). The ESA Medium Resolution Imaging Spectrometer (MERIS): Requirements to its mission and performance of its system. In P. J. Curran and, & Y. C. Robertson (Eds.), RSS95, Remote Sensing in Action, Proceedings of the 21st Annual Conference of the Remote Sensing Society University of Southampton, UK, 11 – 14 September 1995 (pp. 125 – 132). Oxfordshire' Taylor and Francis.

Kahru, M., Raphael, M. K., Clarissa R. A., Manzano-Sarabia, M., & Mitchell, B. G. (2014). Evaluation of Satellite Retrievals of ocean chlorophyll-a in the California current. Remote Sens., 2014, *6*, 8524–8540.

Bailey, S.W., & Werdell, P.J., (2006). A multi-sensor approach for the on-orbit validation of ocean color satellite data products. Remote Sensing of Environment *102* (2006) 12–23

Sarmiento, J. L., Slater, R., Barber, R., Bopp, L., Doney, S. C., & Hirst, A. C. (2004). Response of ocean ecosystems to climate warming. Global Biogeochemistry Cycles, *18*, G3003. doi:10.1029/2003GB002134.

Shang, S.L., Dong, Q., Hu, C.M., Lin, G., Li, Y.H., & Shang, S.P. (2014). On the consistency of MODIS chlorophyll a products in the northern South China Sea. Biogeosciences, 2014, 11.

Swallow, J.C. (1984) Some Aspects of the Physical Oceanography of the Indian Ocean. Deep-Sea Research, *31*, 639-650.

Latha, T. P., Nagamani, P. V., Rao, B. S., Amarendra, P., Rao, K. H., Choudhury, S. B., Dash, S. K., & Sarma, V. V. S. S. (2013). Particle Backscattering Variability in the Coastal Waters of Bay of Bengal: A Case Study Along Off Kakinada and Yanam Regions. IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, VOL. *10*, NO. 6, NOVEMBER 2013.

Tanii, J., Machida, T., Ayada, H., Katsuyama, Y., Ishida, J., & Iwasaki, N. (1991). Ocean Color and Temperature Scanner (OCTS) for ADEOS. In P. N. Slater (Ed.), Future European and Japanese Remote-Sensing Sensors and Programs: Proceedings of the Meeting, Orlando, Fla, April 1, 2, 1991. Proceedings SPIE, vol. *1490* (pp. 200 – 206). Bellingham' The Society of Photo-Optical Instrumentation Engineers.

Tilstone, G.H., Lotliker, A.A., Miller, P.I., Ashraf, P.M., Kumar, T.S., Suresh, T., & Menon, H.B. (2013). Assessment of MODIS-Aqua chlorophyll-a algorithms in coastal and shelf waters of the eastern Arabian Sea. Cont. Shelf Res. 2013, 65.

Tomlinson, M. C., Stumpf, R. P., Ransibrahmanakul, V., Truby, E. W., Kirkpatrick, G. J., Pederson, B. A., et al. (2004). Evaluation of the use of SeaWiFS imagery for detecting Karenia brevis harmful algal blooms in the eastern Gulf of Mexico. Remote Sensing of Environment, 91, 293 – 303.

Vase, V. K., Dash, G., Sreenath, K. R., Shailendra, R., Mohammed, K. K., Divu, D., Dash, S., Pradhan, R. K., Sukhdhane, K. S., Jayasankar, J. (2018). Spatio-temporal variability of physico-chemical variables, chlorophyll a, and primary productivity in the northern Arabian Sea along India coast (2018). Environmental Monitoring and Assessment 190:148.

Werdell J.P., Bailey S., Fargion G., Pietras C., Knobelspiesse K., Feldman G, & McClain C., (2003). Unique data repository facilitates ocean colour satellite validation. Eos, vol, 84, No. *38*, 23 September 2003, pages 377-392.

Werdell, P. J., & Bailey, S. W. (2005). An improved bio-optical data set for ocean color algorithm development and satellite data product validation. *Remote sensing of Environment. 98*, 122-140.

Zhang, C., Hu, C., Shang, S., Müller-Karger, F. E., Li, Y., Dai, M. (2006). Bridging between SeaWiFS and MODIS for continuity of chlorophyll a concentration assessments off southeastern China. Remote Sensing of Environment, *102*, 250−263.